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Perspective

MANAGEMENT OF VECTOR-BORNE DISEASES WITH ARTIFICIAL INTELLIGENCE AND ITS LIMITATIONS

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ABSTRACT

Vector-borne diseases (VBDs) such as malaria, dengue, chikungunya, Japanese encephalitis etc., remain major public health concerns, particularly in densely populated countries like India claiming hundreds of thousands of lives each year. Consequently, their management and prevention are of utmost importance to public health authorities across the world. However, doing so involves various complex challenges relating to a thorough understanding of the interplay between the disease/vector, pathogen, reservoir host and victim,

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as well as complex environmental, ecological, and social phenomena, something that is achievable by human researchers only, with domain-specific expertise obtained through years of training, alongside the expenditure of significant public funds. Such stringent requirements often put economically underdeveloped societies at risk in the event that they are unable to afford the time and resources required to be invested in order to properly understand and manage such diseases. To this end, we propose the usage of the recent advancements in Artificial Intelligence (AI) to plan the management and mitigation of vector-borne diseases. We discuss potential applications of generative AI in developing a better understanding of novel and rare vector-borne diseases, as well as a medium to provide automated assistance to non-experts. Finally, we identify possible challenges that an institution might run into in the process of adopting AI as a way to augment their capabilities in dealing with vector-borne diseases.

INTRODUCTION

According to the World Health Organization (WHO, 2025), more than 17% of all diseases are vector-borne, leading to more than 700,000 deaths annually. Although preventable through various means such as protective measures and community mobilization, they hit some of the most impoverished parts of the world the hardest, often as a consequence of population growth, poor levels of hygiene, etc., caused by rapid urbanization (KNUDSEN & SLOOFF, 1992). It must be noted that such places are economically challenged to begin with, and being burdened with the complexities of having to deal with vector-borne diseases further worsens their situation.

This motivates us to synthesize and assess existing AI-enabled approaches that are already deployed in practice to facilitate the management and control of vector-borne diseases, by improving their understanding with the use of Artificial Intelligence (AI).

We explore the possibility of leveraging AI in studying vector-borne diseases in the context of the vicious cycle of the 4 'Vs': Virus → Vertebrate Host → Vector → Victim, and their interplay with environmental and social factors. Our propositions are subject to the predictability of the variables in question based on climatic and environmental conditions and their strong interconnections to the growth and proliferation of vector-borne diseases, as evidenced in the associated literature (CAMINADE et al., 2019; WU & HUANG, 2022).

For instance, diseases like Japanese encephalitis (JE) can be transmitted only from animals to humans, but not from humans to other humans. Thus, the life cycle of the virus ends in a human. Incidentally, several mosquito species are involved in the enzootic and epizootic cycle of JE. On the other hand, diseases like malaria, dengue, yellow-fever, etc., can be transmitted by humans to other humans, *i.e.*, humans can act as both victims and vectors. In terms of the role of the human immune system, diseases like dengue can be tackled with natural immunity while those like Japanese encephalitis require vaccination. Due to such multitude in variations in propagation patterns, upon the introduction of novel a disease in an ecosystem, its management becomes challenging. Researchers need to wait a certain amount of time to gather sufficient data and conduct lengthy experiments, during which a large number of people already get affected by the disease, before they can be sure of its dynamics. This leads to loss of lives and imposes stress on public funds, putting relatively weaker economies at a categorical disadvantage.

Followed by the scientific analysis comes the aspect of planning for the management of the disease, which requires the involvement of various policymakers and public representatives and typically involve lengthy bureaucratic processes. This further increases the time-to-action leading to additional loss of lives and financial costs. Overall, the significant manual effort involved in the analysis and management of vector-borne diseases has been a part of the process through which societies cope with vector-borne diseases. However, with the recent advancements in AI based on deep learning models such as Convolutional Neural Networks (HE et al., 2015), Recurrent Neural Networks (SCHMIDT, 2019), Transformers (VASWANI et al., 2017; DOSOVITSKIY et al., 2021) etc., and highly effective unsupervised training paradigms (HE et al., 2019; SIM'EONI et al., 2025), this landscape has already begun to change through operational deployments that reduce time-to-action in surveillance, prediction, and intervention planning.

Conditions of water bodies, rain, underdevelopment, ecological degradation resulting from infrastructural growth, lack of vaccination, etc., are all attributes that researchers take into account while studying the growth and proliferation of vector-borne diseases. However, modern deep learning (GOODFELLOW et al., 2016), one of the most promising, emerging subfields of AI based on deep neural networks, provides bespoke algorithms to deal with each of these data types, termed "modalities", often in unison via multimodal models (GIRDHAR et al., 2023; RADFORD et al., 2021). The insights drawn from such AI models can be used to plan the management and control of vector-borne diseases. The intractability of large-scale global challenges like climate change have already prompted researchers to consider the use of AI in studying vector-borne diseases (VECTOR-AI, n.d.). When integrated into established surveillance and decision-making workflows, AI systems have already demonstrated the ability to enhance expert-driven disease management, making the management planning and control of vector-borne diseases more efficient in both time and associated costs.

With this view, we outline a set of key potential focus areas that can benefit from the use of AI, followed by ideations of potential AI-driven solutions for them. However, we recognize that the use of AI does not come without caveats, for which reason, we additionally comment on the challenges in its adoption with regards to combating vector-borne diseases.

1. Focus Areas and Potential Solutions

Here, we outline some of the resource-intensive aspects of vector-borne disease management that demand significant focus, and thus, can potentially benefit from the application of AI. We additionally discuss our thoughts on how effective AI-driven solutions could be potentially developed for tackling the associated issues.

1.1 *Predicting Disease Propagation*

One of the primary steps towards adopting precautionary measures against vector-borne diseases is to model and predict the geographical movement of vectors. We believe that this can be achieved using tools from geometric deep learning (BRONSTEIN et al., 2021) via techniques similar to those that have been developed for weather prediction (LAM et al., 2023) or the modelling of many-body dynamical systems (SHARMA & FINK, 2025). Approaches developed for modelling the spread of misinformation in social networks (PHAN et al., 2023) could also be inspire the modelling the propagation of vector-borne diseases. As an example, GNNs that have been used to model the propagation of COVID-19 (SONG et al., 2023) and pandemics in general (PANAGOPOULOS et al., 2021) can be considered. Related approaches are already used for outbreak forecasting, hotspot identification, and short-term intervention planning in vector-borne disease settings. Based on this, source tracing and root cause analysis of the disease origin can be performed using tools from graph and causal machine learning (MOCCIA et al., 2024).

1.2 *Evaluating Environmental Quality*

Environmental quality is known to be one of the primary determinants of proliferation and propagation of vector-borne diseases. Thus, being able to automate the analysis and monitoring of the environmental quality of a neighbourhood could boost productivity when in comes to vector-borne disease management. Computer vision algorithms based on CNNs (HE et al., 2015), RNNs (GEETHA et al., 2024; SCHMIDT, 2019), and Transformers (DOSOVITSKIY et al., 2021), that can identify and localize contents in visual sources of information such as images and videos are particularly suited for this purpose. They can be deployed for tasks like evaluation of the quality of local water-bodies, hygiene and sanitation of a neighbourhood, detecting presence of vectors of interest, as well as satellite imagery-based monitoring of vector movements across geographical locations to name a few. For instance, some progress has already been made along these lines by the community in tasks like identification of breeding grounds for vectors (SAYEEDI et al., 2024), identification and classification of various vector species (LEE et al., 2023) as well as continuous monitoring using drones, robotic platforms, and citizen-submitted imagery pipelines.

1.3 *Applications of Generative AI*

Large Language Models (LLMs) have lately been shown to exhibit exceptional zero-shot reasoning (KOJIMA et al., 2022) and planning (HUANG et al., 2024) capabilities. On the other hand, diffusion models have shown strong promise in generating high quality visual data (HO et al., 2020). These advances are already being applied in practice to support vector-borne disease surveillance, prediction, and decision support, particularly in settings with limited or imbalanced data. We believe that they can be extremely beneficial when it comes to developing a deeper understanding of vector-borne diseases, as well as in planning for and assisting with their management.

(a) **Modelling novel diseases:** Predicting the potential vicious cycle of the 4 'V's: V̲irus → V̲ertebrate Host → V̲ector → V̲ictim a priori when the virus has just started surfacing.

(b) **Analysis of Rare Vector-borne Diseases:** Generative AI can be used to generate novel samples from the limited data available for rare diseases. The expanded dataset can then be used for down- stream analysis such as predicting propagation patterns, potential habitats, symptoms, etc., and could thereby aid in more informed policy-making.

Generative AI has already been used to augment limited datasets for rare diseases, enabling improved downstream analysis such as predicting propagation patterns, potential habitats, and symptom characterization, while also introducing challenges related to validation, bias, and synthetic–real alignment.

(c) **Material Science for Vector Control:** Tools based on nanotechnology and polymer science is known to have the potential to facilitate the control of vector-borne diseases (BASU & BHATTACHARYA, 2021). For this purpose the, advancements in AI applied to nanotechnology (YANG et al., 2024) and polymer science (CAO et al. 2026) can be leveraged.

(d) **Planning Based on Scientific Data:** Recently, LLMs have demonstrated exceptional autonomous planning abilities in a wide variety of tasks (HUANG et al., 2024), complementing existing AI-assisted decision-support systems that are already used to prioritize and trigger public-health interventions in practice. This capability can thus be used to produce plans, in collaboration with human actors, for managing a vector-borne disease given local environmental and ecological conditions, economic constraints, and other kinds of information about the disease itself such as growth and proliferation patterns, individuals who are particularly vulnerable, etc.

(e) **Automated Assistance and Help Desks:** LLMs can be used to provide detailed information about diseases in a locality and their spreading patterns in an accessible manner readily to anyone seeking the same. This would be particularly helpful in catering to non-experts such as local citizens or tourists planning to travel to an area, who constitute the majority of the population, allowing them to readily learn about and take measures to prevent themselves from getting affected by the diseases in question.

LLMs are already incorporated into public-facing and citizen-assistance platforms to provide accessible, localized information about diseases and prevention measures, with increasing emphasis on expert validation, multilingual support, and human-in-the-loop moderation.

2.1 Challenges in the Adoption of AI

2.1 *Dataset Construction*

State-of-the-art deep learning architectures like Transformers (VASWANI et al., 2017; DOSOVITSKIY et al., 2021), although highly performant, require a vast amount of data to train (KANDPAL & RAFFEL, 2025). This is due to the lack of inductive biases in the architecture, which allows the model to discover patterns from the data directly. Although it provides flexibility/ adaptability to the domain, in the absence of sufficient training data, the models could suffer from overfitting, leading to poor generalization. Thus, the application of modern AI to the study and management of vector-borne diseases for which sufficient data is not available could be infeasible. If the disease in question has characteristics similar to others for which sufficient data is available, then, the zero-shot learning capabilities (KOJIMA et al., 2022; RADFORD et al., 2021) of modern AI can be leveraged. However, if the disease in question differs significantly from all others, then, even the zero-shot learning avenue may not yield useful results.

Thus, while data availability remains a concern, practical deployments increasingly mitigate data limitations through citizen-science data collection, transfer learning from pretrained models, public datasets, and data augmentation techniques, shifting the primary challenge toward data quality, representativeness, governance, and sustained curation.

2.2 *Computational Resources*

The cost of training modern AI models is extremely high, *i.e.*, in the millions of dollars (COTTIER et al., 2024), and is steadily increasing as model sizes grow (KANDPAL & RAFFEL, 2025). This makes it prohibitive for already struggling economies to develop custom large AI models for their domestic vector-borne disease-related challenges. Although fine-tuning methods based on Low Rank Adaptation (LoRA) (HU et al., 2022) and Mixture-of-Experts (MoE) (ARTETXE et al., 2021) can be cost-effective alternatives, they too can turn out to be expensive (XIA et al., 2024) for marginalized economies.

However, most deployed vector-borne disease systems rely on efficient architectures operating on edge devices or pretrained models deployed via cloud inference, substantially lowering practical deployment barriers, even in resource-constrained settings.

2.2 *Explainability*

It is well known that due to the complexities in modern AI systems based on deep neural networks, clearly elucidating what function/ algorithm they have learned from the data and explaining their decision-making process is a yet unsolved problem (XU & YANG, 2025). Although significant efforts are being put towards decoding the inference mechanisms and the algorithmic logic learned by deep neural networks (BERESKA & GAVVES, 2024), progress still needs to be made in scaling them to larger models that are used in practice. Primarily, this becomes a roadblock in understanding the inference mechanisms of the AI model, something that is imperative for life-critical applications like vector-borne disease management. Further, it poses a challenge in ensuring the alignment of model predictions with the opinion of vector-borne disease experts, which is necessary if AI models are to augment the capabilities of human experts.

In practice, explainability challenges are commonly addressed through human-in-the-loop system designs, including expert verification, dashboard-based monitoring, confidence estimates, and localized visual explanations, allowing safe operational deployment despite incomplete model interpretability.

CONCLUSION

In this work, we identified several key focus areas in vector-borne disease analysis and management that could potentially benefit from the application of modern AI. Directly impacting the management planning and control of vector-borne diseases is the ability to predict disease propagation using graph and causal machine learning, as well as the continuous monitoring/ evaluation of environmental quality with tools from computer vision. In addition to this, there are several potential areas, some pertaining to the analysis of vector-borne diseases that could leverage the capabilities of generative AI. These include the modelling of novel or rare diseases to facilitate further understanding, developing techniques for better disease control, etc.

While there is substantial real-world progress and deployment maturity, the adoption of AI for vector-borne disease management continues to face open challenges related to generalization, governance, robustness, and sustained oversight.

However, we simultaneously highlight the fact that the application of AI to these problems does not come without limitations. Several challenges like access to high-quality datasets, high computational resource demand, the non-transparent nature of modern AI systems, to name a few, could be significant hurdles that institutions considering the adoption of AI for vector-borne disease analysis and management need to take into account.

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